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Intervention analysis to assess advertising effectiveness on brand awareness

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1 Introduction

In the past decades, a huge amount of literature has been devoted to the estimation of the effects of advertising on sales using field data (Leone and Schultz, 1980; Vakratsas and Ambler, 1999) and metanalyses of these studies have shown that advertising effects greatly vary by market and product characteristics (Assmus, Farley and Lehmann, 1984; Sethuraman and Tellis, 1991). Moreover, recent studies based on single source data have also found significant effects of advertising (Deigthon, Henderson and Neslin, 1994; Kanetkar, Weinberg and Weiss, 1992; Pedrick and Zuyfriden, 1991; Tellis and Weiss, 1995).

However, we cannot stop at behavioral responses, for one obvious reason. Short-term sales measures, including those from single-source panels, can only apply to frequently purchased products, but increasing amounts of advertising are devoted to occasional purchases, or to aims which are not purchases at all, but beliefs and opinions. For these, we have to look how people respond in thoughts and feelings, rather than actions.

For this goal, the use of intermediate variables such as awareness, recall and image can act as surrogates for sales in assessing advertising effectiveness, and many researches have been developed for building advertising scheduling models, aiming to identify conditions under which different types of media dynamic scheduling strategies are optimal (Zielske, 1959; Strong, 1974 and 1977; Zielske and Henry, 1980; Simon, 1982; Mahajan and Muller, 1986; Naik, Mantrala and Sawyer, 1998; Tellis, Chandy and Thaivanich, 2000).

In this study, we apply intervention analysis in the context of assessing the effectiveness of a television advertising policy. In particular, we consider the flights emitted by some car brands in a certain period as time series of deterministic events that influence awareness of advertising of the same car brands. Our aim is to detect which flights are really effective in determining brand awareness and how great the magnitude of their impact is. To do that, we base on intervention analysis focusing on one of the 'points worthy of note' that Box and Tiao (1975, pag. 72) suggest to develop:

> Intervention extending over several time intervals can be represented by a series of pulses. A three months advertising campaign might be represented, for example, by three pulses whose magnitude might represent expenditure in the three months.

Time series are often influenced by special events of deterministic and exogenous nature referred to as intervention events. The method to account for the expected effects of these events is known as intervention analysis, introduced by Box and Tiao (1975) in the context of *ARIMA* models developed by Box and Jenkins (1970). In the setting of intervention analysis, it is assumed that an intervention event has occurred at a known point in time of a time series. It is of interest to determine wether there is any evidence of a change or effect, of an expected time, on the time series under study, associated to the event. To model the nature and estimate the magnitude of the effects of an intervention, *i.e.* to account for the possible unusual behavior in the time series related to the event, transfer function models are often used.

Our basic assumption is that the series of brand awareness is generated by a linear process and that its level variations as well as its local maxima are caused by deterministic interventions, namely, the advertising flights. It has to be remarked that the primary scope of this study is not to *represent* a response variable (advertising recall) through an input (the flights) but to detect *which* inputs, among a plurality, are most significant and *how great* their impact is on the response variable. So the results

of the analysis allow to identify the combinations of creative ads, Tv stations used, time schedule adopted within the day and the week, that show a significant effect on recall. Obviously, this approach can be adopted with other output variables that are linked to advertising, as, for instance, recognition, image, preferences.

The aim of the study justifies the methodological choice of intervention analysis, rather than regression methods (furthermore non appropriate for serially dependent data as time series) or Student' test for estimating and testing a change in mean. Besides, when using data with weekly or daily frequency to avoid data interval bias (Clarke, 1976; Tellis and Weiss, 1995), the pulsing pattern of the advertising schedule makes the regression approach less effective in detecting advertising effect.

The rest of the paper is structured as follows. In Section 2 we introduce the theory of intervention analysis in the context of *ARIMA* modelling: the general forms of the stochastic and of the deterministic term of an intervention model are considered. In Section 3, we trace the main lines of our analysis, *i.e.* we identify and comment the intervention models that best describe the observed time series of brand awareness. In Section 4 some concluding remarks on the power of intervention analysis in advertising models are reported. Figures and Tables are all reported after the References.

2 The intervention model

The general form of an intervention model for a response variable y_t in the presence of dependent noise structure is the following:

$$y_t = N_t + \mathcal{Y}_t \tag{1}$$

where N_t is a stochastic process representing the background observed series y_t without the intervention, while $\mathcal{Y}_t$ represents the effects of the intervention events in terms of some deterministic input series. The two processes N_t and $\mathcal{Y}_t$ are uncorrelated, being one stochastic and the other deterministic.

The stochastic component N_t can be represented by a seasonal autoregressive integrated moving average process *SARIMA (p,d,q) (P,D,Q)*:

$$N_t = \frac{\theta_0 + \Theta_Q(B)\,\theta_q(B)\,a_t}{\Phi_P(B)\,\phi_p(B)\,(1-B)^D\,(1-B)^d}$$

where B is the backshift operator such that $By_t = y_{t-1}$; $\{a_t\}_{t=1,\dots,n}$ is a white noise process, *i.e.* a sequence of uncorrelated variables with zero mean and constant variance $\sigma_a^2 < \infty$; $\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$ and $\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$ are the autoregressive and moving average polynomials of degree p and q respectively, and $\Phi_P(B) = 1 - \Phi_1 B^s - \Phi_2 B^{2s} - \cdots - \Phi_P B^{Ps}$ and $\Theta_Q(B) = 1 - \Theta_1 B^s - \Theta_2 B^{2s} - \cdots - \Theta_Q B^{Qs}$ are their seasonal counterpart (s: seasonal periodicity); $\theta_0\left[\Phi_P(B)\,\phi_p(B)\,(1-B)^D\,(1-B)^d\right]^{-1}$ is a constant that represents the mean of the series while $d \geq 0$ and $D \geq 0$ are the orders of the regular and seasonal differences to be taken in order to make the series stationary. To be uniquely identified, the above model must be stationary and invertible and these two conditions are fulfilled if the roots of the above polynomials all lie outside the unit circle.

The deterministic function $\mathcal{Y}_t$ can be represented by a dynamic model of the form

$$\mathcal{Y}_t = \sum_{j=1}^{z} \mathcal{Y}_{tj} = \sum_{j=1}^{z} \frac{\omega_j(B)}{\delta_j(B)}\xi_{tj}$$

where $\mathcal{Y}_{tj}$ represents the dynamic transfer from each of the z input series ξ_{tj}; $\frac{\omega_j(B)}{\delta_j(B)}$ is the transfer function expressed as the

ratio of two polynomials $\omega_j(B) = \omega_{0j} - \omega_{1j}B - \cdots - \omega_{rj}B^{r_j}$ and $\delta_j(B) = \delta_{0j} - \delta_{1j}B - \cdots - \delta_{mj}B^{m_j}$ of degree r_j and m_j respectively and the roots of $\omega_j(B)$ lie outside the unit circle while the roots of $\delta_j(B)$ lie outside or on the unit circle. In wide generality, the individual ξ_{tj} could be any exogenous time series whose influence needs to be taken into account, but in practice, there are two common types of deterministic input variable that well represent the impact of intervention events on a time series. Both of these are indicator variables taking only the values 0 and 1 to denote the nonoccurrence or occurrence of intervention. For a temporary or transient intervention that will die out after time T, a pulse variable $P_t^{(T)}$ is adequate:

$$P_t^{(T)} = \begin{cases} 1 & t = T \\ 0 & t \neq T \end{cases} \tag{2}$$

while for an intervention that is expected to remain permanently in the interval $T \leq t \leq T+k-1$ to some extent, a step variable $S_t^{(T,k)}$ is to be chosen:

$$S_t^{(T,k)} = \begin{cases} 1 & T \leq t \leq T+k-1 \\ 0 & t < T \,\cup\, t > T+k-1 \end{cases} \tag{3}$$

and k is the length of the interval.

Several response patterns are possible through different choices of each transfer function, according to the selection of the variables ξ_{tj} and to various combination of the degrees of the polynomials $\omega_j(B)$ and $\delta_j(B)$ (see Box, Jenkins and Reinsel, 1994, Part III). For intervention events that produce an immediate impact at a time T followed by a gradual decay back to the original pre-intervention level with no permanent effect, as is the case of some flights advertising campaigns, a suitable transfer function is the following:

$$\mathcal{Y}_{tj} = \frac{\omega_j}{1-\delta_j B}P_t^{(T)} \tag{4}$$

where ω_j is the unknown magnitude of the sudden increase of y_t due to the variable ξ_{tj} and $\delta_j \in (0,1)$ is the rate of gradual decay.

It follows by

$$\begin{aligned}\mathcal{Y}_{tj} &= \omega_j (1-\delta_j B) P_t^{(T)} = \omega_j \left(1+\delta_j B + \delta_j^2 B^2 + \ldots\right) P_t^{(T)} = \\ &= \omega_j \left(P_t^{(T)} + \delta_j P_{t-1}^{(T)} + \delta_j^2 P_{t-2}^{(T)} + \ldots\right) = \\ &= \omega_j P_t^{(T)} + \omega_j \delta_j P_t^{(T+1)} + \omega_j \delta_j^2 P_t^{(T+2)} + \ldots\end{aligned}$$

that $\mathcal{Y}_{tj}$ produce an increase of size ω_j at time T, followed by an increase of size $\omega_j\delta_j < \omega_j$ at time $T+1$ and so on till coming back to the level before time T. In general, we will truncate the above expansion after k lags, such that the value of the input variable ξ_{tj} is equal to zero when $t > T+k$, *i.e.*

$$\omega_j (1-\delta_j B) P_t^{(T)} = \omega_j \left(P_t^{(T)} + \delta_j P_t^{(T+1)} + \ldots + \delta_j^k P_t^{(T+k)}\right)$$

and k is the length of the flight.

In the present study, the response variable y_t is represented by the advertising recall whose value at a time t is supposed to depend on its past values $y_{t-1}, y_{t-2}, \ldots$, on current and past innovations of stochastic nature, $a_t, a_{t-1}, \ldots$, and on some deterministic variables $\mathcal{Y}_{tj}$ represented by the flights. These latter are deterministic by definition, since their emission is the result of a programmatic advertising campaign.

In the following section we concentrate on the identification of the model which better describes the response variable y_t, by choosing the most adequate $SARIMA$ model for the stochastic part N_t and the appropriate intervention model for the deterministic part $\mathcal{Y}_t$ and we evaluate the most significant intervention events.

3 The analysis

The response variables y_t considered in this study are time series of weekly data obtained aggregating the percentage of awareness of various car brands deriving by daily phone interviews on random samples of Italian families (source: Promocentro-Milano). The data have been collected by phone interviews (350 a day). The measure of advertising effectiveness is advertising recall or awareness, which is measured through the following question: "Which brands of cars have you seen advertised on television recently?". Awareness is consistent with theoretical models of advertising effectiveness, such as that of Nerlove and Arrow (1962). The input variables are the television flights represented by the Gross Rating Points (GRP), which are a measure of advertising pressure (sources: AGB and Marketing TV Service). For both the variables, we dispose of five data sets relative to five different brands of cars, covering near the the 80% of the middle segment of cost: Renault Clio, Opel Corsa, Peugeot 206, Ford Fiesta, Fiat Punto. The ten series correspond to the same time period, running from 1 February 1999 to 30 October 2000, for a total of 92 observations for each series.

These data are appropriate to test our method for the following reasons. Advertising tracking data are widely used by advertisers and are considered to be helpful in determining advertising effectiveness (Rossiter and Percy, 1997). Furthermore, advertising recall is likely to reflect prior noting and possessing of advertising.

3.1 The stochastic term

To identify the $SARIMA$ process supposed to generate the stochastic term of the series of brand awareness, we follow the standard Box and Jenkins (1970) iterative procedure consisting of four steps: (i) preliminary analysis of the observed series, (ii) identification of a $SARIMA$ model, (iii) estimation of the parameters, (iv) diagnostic checking. If (iv) shows no inadequacy in the model, then appropriate inferences can be lead; otherwise, if serious deficiencies are uncovered, it is necessary to make adequate model modifications or to repeat the analysis from (i).

(i) The *preliminary analysis* consists in some graphical inspections and transformations of the original time series to detect and remove a nonstationarity due to trend or seasonality. Figures 1 to 5 show the graphs of the original series of awareness for the five brands considered. No trend or seasonality is apparent in any series, but sudden changes such as local maxima and level variations are evident, especially in Fig. 1, 4 and in Fig. 3, 5 respectively. The nonstationarity inducted by these structural variations will be modeled with the interventions, coherently with the hypothesis that it is of deterministic nature. The graphics of the autocorrelation functions of the original series (not reproduced here) confirm the stationarity of the series since for all of them the global autocorrelation function shows a quick exponential decay.

(ii) Because no trend nor seasonal pattern have been detected in (i), the *identification* of the process representing the stochastic part of y_t is restricted to the class of the $ARMA\,(p,q)$ models and it is done through the autocorrelation functions of the stationary series. Since the global autocorrelation function of all the series shows a rapid exponential decay and the partial autocorrelation function dies after the first lag, we hypothesise that the series follow an $AR\,(1)$ process. This is coherent with the theory of exponentially decay of advertising effect on recall as stated by Zielske (1959), Zielske and Henry (1980) and Broadbent (1979, 1990, 1997).

(iii) The *estimation* of the parameters of the model is made with the maximum likelihood method. We have proceeded au-

tomatically with the software SPSS 10.0. For all the series, the estimated autoregressive coefficients ϕ and the constants of level μ are significant at the level $\alpha = 0.001$, according to the Student's t statistics. In Table 1, for each response variable (brand awareness) we indicate the values of the estimates (B), together with those of: the standard errors (SEB), the Student's t statistics (T-RATIO) and the corresponding p-values (APPROX.PROB.). The estimated value of the autoregressive parameter (AR1) is, for all the series, about 0.8: this means that awareness is highly influenced by its preceding value, as we expected. Concerning the estimated mean level of the process (CONSTANT), we observe that the highest is shown by Punto ($\theta_0 = 8.80$) and it is probably determined by variables that we do not take into account in this study. Furthermore, before drawing any conclusion, the adequacy of the identified models must be evaluated.

(iv) The *diagnostic checking* consists in the analysis of the residuals of the identified model: for a good fitting, they must be uncorrelated, while for a good forecasting performance, they also must be normally distributed. Since at this stage we are not interested in the predictive performance of the identified models, we only test the null hypothesis of absence of correlation among the residuals. The test-statistics is the Box-Ljung test for the null hypothesis $H_0 = \rho_1 = \rho_2 = \cdots = \rho_K$ where ρ_k is the autocorrelation coefficient among the residuals at lag k, with $k = 1, \cdots, K$. We have chosen $K = 48$. This high number of lags corresponding to quite a year of weekly data allows to detect some significant correlations at late lags, that we expect to meet because of the sudden variations of level observed in the original series. In fact, even if the Box-Ljung is never significant at the level $\alpha = 0.05$ for any series (the corresponding p-values are all greater than 0.4, except that of ρ_2 for the residuals of Punto, whose is equal 0.052 and anyway also not significant) some autocorrelation coefficients are significantly out of the confidence bounds given by 2σ, where σ is the standar error of each estimate. This can be directly seen in Fig. 6 to 10 which show the graphs of the global autocorrelation functions of the residuals of the $AR(1)$ models (the partial autocorrelation functions, not reported here, show a similar pattern). The models chosen seem to be adequate, since nonzero autocorrelations at lags 8, 27, 38, 31, 32 (respectively in Fig. 6, 8, 8, 9, 10) do not reveal any systematic behavior, where for systematic we mean: autoregressive of order p (in this case there would be significant global autocorrelations at lags $1, \ldots, p$); moving average of order q (significant partial autocorrelations at lags $1, \ldots, q$); a seasonal pattern (significant autocorrelations every s lags); trading day variations (not sensible in weekly data).

These significant autocorrelations, even not affecting the choice of the stochastic process generating the series, are synthomatic of some anomaly in the series which indeed induces to consider the hypothesis that it is influenced by some deterministic events. The behavior of the residuals, represented in Figures 11 to 15, confirms the adequacy of the models together with the need of some interventions, since they show a random pattern around a null mean with constant variance, except for many extreme points that witness the sudden level changes in the original series (the bold points represent the extreme values of the residuals that, as we will see, will be corrected by the interventions). This will be considered in the following section.

3.2 The deterministic term

In flights advertising campaigns, such as those illustrated by the time series in Figures 16 to 20, each flight can be interpreted as an intervention event. However, we guess that not all the flights have a straight impact on the series of awareness and indeed our aim is to detect *which* flights are the most effective (*i.e.* enter

significantly in the model) in the context of a specific advertising policy. Hence we proceed as follows.

Let z be the number of flights a campaign is made of, each one of length k: for example, in Fig. 16, $z = 10$ and $k = 4$. Corresponding to each jth flight $\mathcal{Y}_{tj}$, we estimate the value of ω_j and evaluate if its impact on the series y_t is significant, when the variable ξ_{tj} chosen is:

(a) a pulse variable that we indicate as $P_{th}^{(T)}$, where h indicates the number of the flight at which we intervene, with $r_j = m_j = 0$, when $k = 0$;

(b) a step variable $S_{th}^{(T,k)}$ with $r_j = m_j = 0$, or

(c) a decreasing variable $(1 - \delta_{tj}B)^{-1} P_{th}^{(T)}$ with $\delta_{tj} \in (0,1)$ known when $k > 0$.

The procedure is the following:

(1) test the significancy of all the flights simultaneously included in the model as pulses or steps according to their length being 1 or greater than 1 respectively;

(2) repeat (1) using decreasing variables instead of steps, choosing for δ_{tj} all the values of the set $\{0.1, 0.2, \ldots, 0.9\}$.

The results of (1) and (2) show that it **never** happens that all the flights are jointly significant; on the other hand, they are informative about the flights that are always significant and those that are never. Hence:

(3) test the significancy of a huge variety of sensible combinations (according to the results given in (1) and (2)) till finding the 'best' intervention model of the form (1), where for 'best' intervention model it is meant the one that restitutes significant parameters both for the stochastic and for the deterministic part and an acceptable behavior of the residuals, together with a sensible correction of the sudden variations influencing the original series. The results are in Table 2: they will be illustrated and commented in the following sections.

3.3 The estimated models

To interpret the results of Table 2, some preliminary remarks need.

In first instance, it has to be stressed that the parameters of the stochastic and those of the deterministic part of the models are estimated simultaneously: as a consequence, the estimate of the constant has affected by the presence of the deteriminstic variables.

The response variable y_t is the brand recall for the five brands considered and in Table 2 is indicated with the name of the brand: CLIO, CORSAR, 206, FIESTA, PUNTO.

The input variables $\mathcal{Y}_{tj}$ are called regressors: each one's name in Table 2 is a summary of its characteristics, such as its position as a flight (flight number), its nature (pulse, step or decreasing variable), its length (except for pulses) and the value of the rate of decay (for decreasing variables only). The single characteristics of each input variable are denoted as follows:

FLh := Flight number h.

STk := Step variable of length k.

Dy := Value of δ_j in model (4), $\delta_j \in \{0.1, 0.2, \ldots, 0.9\}$.

P := Pulse variable.

As an example, consider the first variable. The response variable CLIO is awareness y_t of the brand Clio and its mean level is estimated to be equal to 2.92 while the estimate of the autoregressive parameter is $\phi_1 = 0.82$, both with a level of significance $\alpha = 0.001$; the regressors representing the input variables are the following: $\mathcal{Y}_{t1}$ is an intervention variable of the form (4) with $\delta_1 = 0.7$ in correspondence of the fourth flight, starting at $T = 29$ and lasting three weeks, whose magnitude is estimated to be $\omega_1 = 1.62$; $\mathcal{Y}_{t2}$ is a step variable of length $k = 7$ at flight $h = 5$ starting at $T = 39$ with $\omega_2 = 1.38$; $\mathcal{Y}_{t3}$ is a step of length $k = 3$ at flight $h = 8$ of estimated value $\omega_3 = 1.28$. The significance level of the deterministic variables is 0.05. Hence, the intervention model estimated for awareness of the brand Clio, say y_t is

$$\begin{aligned} y_t &= 2.92 + (1 - 0.82B)^{-1} a_t + \\ &+1.62 \left(P_{t4}^{(29)} + 0.7P_{t4}^{(30)} + 0.49P_{t4}^{(31)} \right) + \\ &+1.38S_{t5}^{(39,7)} + 1.28S_{t8}^{(60,3)}. \end{aligned}$$

The same procedure can be applied to each variable and to the corresponding estimates in Table 2 to get intervention models for each of the brands considered. Hence, the estimated models for Corsa, 206, Fiesta, Punto are respectively:

$$\begin{aligned} y_t &= 1.80 + (1 - 0.74B)^{-1} a_t + 0.95S_{t6}^{(30,2)} + 1.28S_{t11}^{(56,3)} + \\ &+1.39S_{t15}^{(91,2)}. \\ y_t &= 1.88 + (1 - 0.88B)^{-1} a_t + 1.17 \left(P_{t2}^{(38)} + 0.7P_{t2}^{(39)} \right) + \\ &+1.28P_{t6}^{(67)} + 1.40S_{t10}^{(84,7)} \\ y_t &= 1.23 + (1 - 0.73B)^{-1} a_t + \\ &+0.96 \left(P_{t5}^{(37)} + 0.7P_{t5}^{(38)} + 0.49P_{t5}^{(39)} + 0.34P_{t5}^{(40)} \right) + \\ &+0.82S_{t7}^{(58,7)} \\ y_t &= 7.12 + (1 + 0.69B)(1 - 0.73B)^{-1} a_t + 2.79P_{t5}^{(17)} + \\ &-2.89P_{t6}^{(32)} + 4.98S_{t10}^{(61,30)}. \end{aligned}$$

We are not interested here in the fitting and forecasting performances of the above estimated processes, since our prime aim is not in modelling brand awareness in view of the flights, but in assessing the flights that are significant and the magnitude of their impact.

Therefore, we first compare the models without the intervention with the intervention models. The only stochastic term that modifies when deterministic variables are included is that of Punto, for which an $ARMA(1,1)$ model seems to be more appropriate than a simple $AR(1)$. This result is not so surprising: the original series of Punto (Fig. 5) shows a more variable path than that of all the other series, inducing to suspect the presence of a more complex structure for the casual innovations, represented by the moving average coefficient for a_{t-1} whose estimate in Table 2 is given by the MA1 term. For the remaining series, the estimates of the autoregressive coefficients and of the constants of the intervention model (Table 2) do not wander off those of the model without the intervention (Table 1): this suggests that the estimates are robust and the model is stable.

We now consider the residuals. On a first glance, the autocorrelation function of the residuals of the intervention models (Fig. 21 to 25) do not seem to behave better than those from the models without (Fig. 6 to 10). This is not so surprising since the model without the intervention was already found to be quite adequate. However, comparing the time series of the residuals with and without the intervention (Fig. 26 to 30 and 11 to 15, respectively), it is evident (see the thick markers $\diamond$) that the sudden variations at the time point corresponding to the interventions have been corrected: so, the interventions have been significant even on the practical point of view of catching the variations. The fact that the residuals of the models with the intervention still are not purely random and stationary just tells that the models chosen are not the best in terms of fitting, and this is a thing we are aware of.

Let now enter in the final part of the analysis, concentrating on the significant flights. These are represented by the bold lines in Fig. 16 to 20 and their effect on the brand awareness is represented by the bold lines in Fig. 1 to 5. For all the series, the number of significant flights is less than or equal to three and in general, the significant flights are:

* those which follow periods of silence or very small transmission, as it can be seen in Fig. 17, I, III; Fig. 18, III; Fig. 19, I and Fig. 20, II;

* those of very high intensity, as is the case of Fig. 19, II and Fig. 20,

* those of long lasting, as, for instance, III of Fig. 20 which can even be identified in a unique step lasting till the end of the period considered.

In particular, the first two interventions produce temporary increases manifested by local maxima, whereas the third generate a durable increase manifested in a change of level, as the bold lines in the original series show (Fig. 1 to 5).

The first significant flight usually manifests itself after three to five flights (Fig. 16,17,19,20), or, in one case, after a single flight that follows a period of silence (Fig. 18). This seems to confirm the lagged effect of a flights advertising campaign in brand awareness on one hand and, on the other hand, the power of flights that follow a period of low transmission.

According to the nature of the flights in relation to the deterministic variables that represent them (pulses, steps, or decreasing functions), we trivially verify that steps produce a more durable effect on the response variable than that of pulses: the longer the step, the higher the level increase (see in particular the last long step of Punto which produces an increase in the series amounting to the 50% of the mean level of the series). If decreasing flights following the model (4) are preferred, then they show to have a significant impact if the value of the decreasing rate δ_j is equal to 0.7. The latter is the only value for δ_j that is significant in all the series in which a model as (4) is estimated to be appropriate.

The magnitude of the impact on the response variable seems not to depend on any of the considered factor and indeed it probably depends on the intensity of the GRPs themselves.

4 Conclusions

The contributions of the present paper concern two different aspects.

Our potential contribution to the practice of media scheduling is that we offer an implementing method that allows media planners to determine which flight can be really effective in shaping brand awareness. The model gives managers a strong framework to evaluate the role of advertising in promoting a source or a product and to evaluate its effectiveness fairly precisely. In particular, the method we propose highlights flights (and so creative ads, stations and week and day scheduling) that are highly effective versus those that are ineffective.

From the normative point of view, the most relevant information that this study provides is the following: in the context of a flight policy, to increase the level of recall at a time t is equivalent to emit a relevantly *higher* flight at time t or to emit a relevantly *lower* flight at time $t-1$. Of course, in the second case the costs will be relevantly reduced. On the other hand, to produce a durable increase in the level of recall, a long, continuative and intense flight seems to be the best thing to do. This last observation, if reversed, can be interpreted as a warning: a long and continuative period of silence may cause a fall of the recall, especially if concurrent brands continue their advertising policies.

The guideline then emerging is that a flight policy made of a reduced number flights but collocated in the 'right' positions may have the same effects on brand awareness of a more expensive and less aimed, even though consistent, advertising campaign.

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Fig. 1 - 5 TIME SERIES OF BRAND AWARENESS

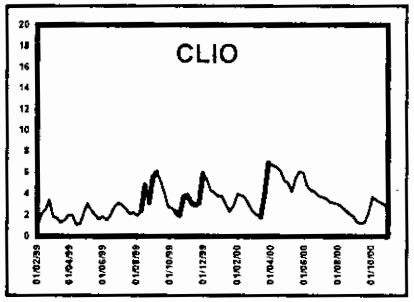

Fig. 1

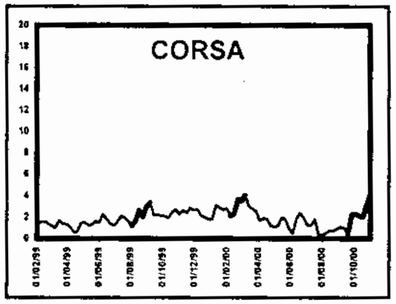

Fig. 2

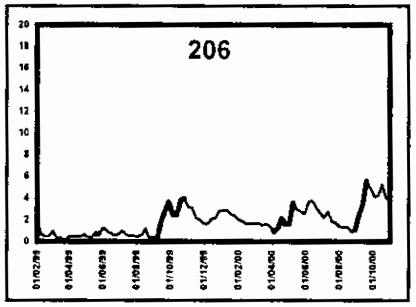

Fig. 3

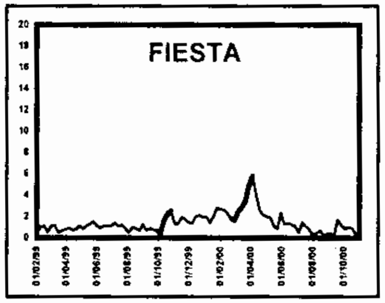

Fig. 4

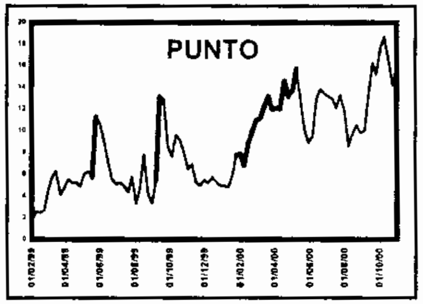

Fig. 5

TABLE 1 AR(1) MODELS

Variable: CLIO

	B	SEB	T-RATIO	APPROX. PROB.
AR1	,8180592	,05893443	13,880838	,0000000
CONSTANT	3,0957944	,46064549	6,720557	,0000000

Variable: CORSA

	B	SEB	T-RATIO	APPROX. PROB.
AR1	,7880274	,07012827	11,236943	,0000000
CONSTANT	1,9373359	,25089489	7,721703	,0000000

Variable: 206

	B	SEB	T-RATIO	APPROX. PROB.
AR1	,8824327	,04999748	17,649544	,00000000
CONSTANT	2,0000809	,50003784	3,999859	,00012976

Variable: FIESTA

	B	SEB	T-RATIO	APPROX. PROB.
AR1	,8264546	,05856699	14,111272	,00000000
CONSTANT	1,3133257	,30702545	4,277579	,00004699

Variable: PUNTO

	B	SEB	T-RATIO	APPROX. PROB.
AR1	,9160123	,0430912	21,257539	,00000000
CONSTANT	8,8022377	2,0097449	4,379779	,00003202

Fig. 6 - 10 CORRELOGRAMS FOR ERRORS FROM THE AR(1) MODELS

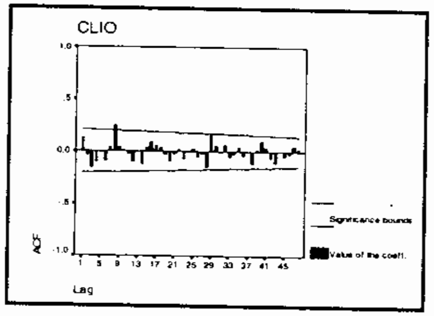

Fig. 6

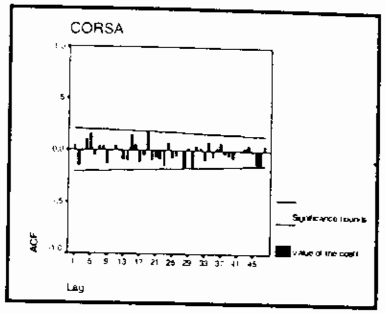

Fig. 7

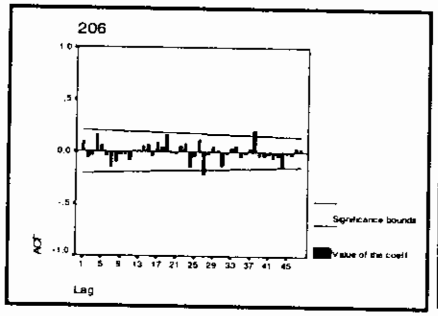

Fig. 8

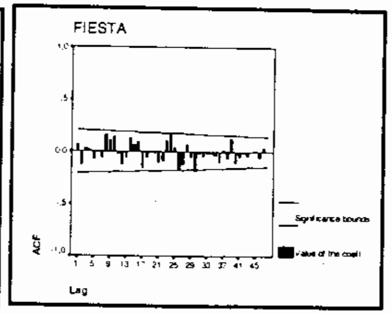

Fig. 9

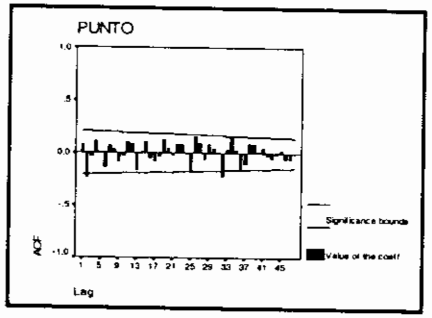

Fig. 10

Fig. 11 - 15 ERRORS FROM THE AR(1) MODELS

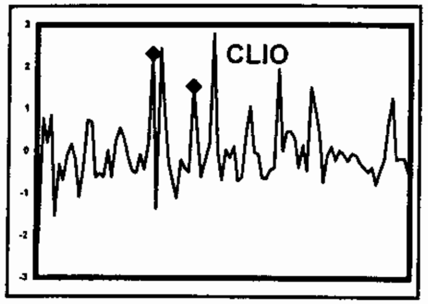

Fig. 11

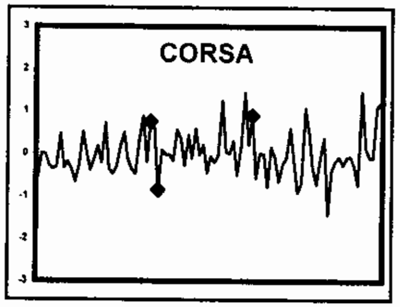

Fig. 12

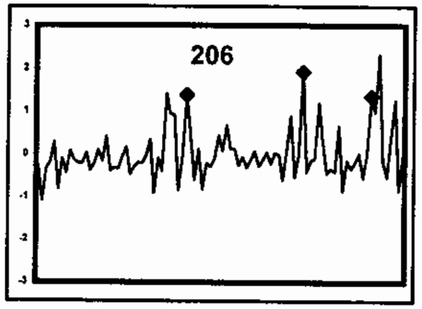

Fig. 13

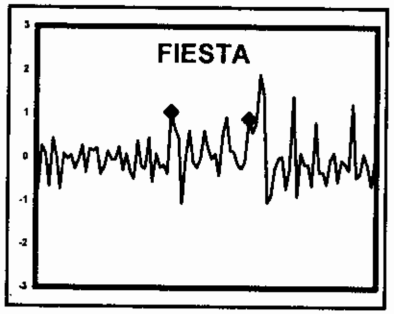

Fig. 14

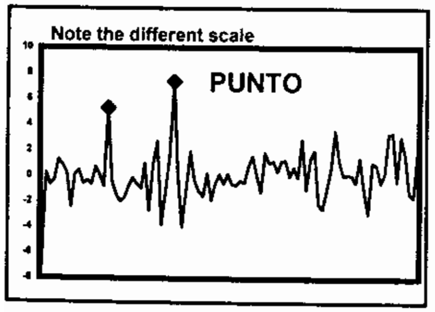

Fig. 15

TABLE 2 INTERVENTION MODELS

Variable: CLIO
Regressors: FL4D07K3
FL5STK7
FL8STK3
Non-seasonal differencing: 0
No seasonal component in model.

Variables in the Model:

	B	SEB	T-RATIO	APPROX. PROB.
AR1	,8216090	,05822702	14,110443	,00000000
FL4D07K3	1,6247679	,72733548	2,233863	,02805633
FL5STK7	1,3759918	,58143847	2,366530	,02017549
FL8STK3	1,2778513	,60034110	2,128542	,03611939
CONSTANT	2,9246103	,44320112	6,598833	,00000000

Variable: CORSA
Regressors: FL6STK2
FL11STK3
FL15STK2

Non-seasonal differencing: 0
No seasonal component in model.

Variables in the Model:

	B	SEB	T-RATIO	APPROX. PROB.
AR1	,7375730	,07119011	10,360610	,00000000
FL6STK2	,9538019	,37143476	2,567885	,01193910
FL11STK3	1,2846033	,36412550	3,527914	,00067143
FL15STK2	1,3865866	,45940435	3,018227	,00333515
CONSTANT	1,7956317	,18368749	9,775471	,00000000

Variable: 206
Regressors: FL2D07K2
FL6P
FL10STK7

Non-seasonal differencing: 0
No seasonal component in model.

Variables in the Model:

	B	SEB	T-RATIO	APPROX. PROB.
AR1	,8818753	,05109150	17,260706	,00000000
FL2D07K2	1,1679171	,43424640	2,689526	,00857640
FL6P	1,2833271	,39943658	3,212843	,00184356
FL10STK7	1,4013870	,39100858	3,584031	,00055737
CONSTANT	1,8761182	,43681048	4,295039	,00004528

Variable: FIESTA
Regressors: FL5P
FL7STK7

Non-seasonal differencing: 0
No seasonal component in model.

Variables in the Model:

	B	SEB	T-RATIO	APPROX. PROB.
AR1	,7347117	,06868998	10,696053	,00000000
FL5D07k4	,9644163	,40401678	2,387070	,01912443
FL7STK7	,8189533	,38651122	2,118835	,03692238
CONSTANT	1,2295242	,19722786	6,234029	,00000002

Variable: PUNTO
Regressors: FL5P
FL6P
FL10STK30

Non-seasonal differencing: 0
No seasonal component in model.

Variables in the Model:

	B	SEB	T-RATIO	APPROX. PROB.
AR1	,5875191	,09643768	6,0922151	,00000003
MA1	-,6953450	,08766738	-7,9316281	,00000000
FL5P	2,7889747	,76195248	3,6603000	,00043396
FL6P	-2,8907965	,76195106	-3,7939399	,00027510
FL10STK30	4,9804361	,98715661	5,0452340	,00000250
CONSTANT	7,1279873	,73760439	9,6636997	,00000000

Fig. 16 - 20 TIME SERIES OF ADVERTISING FLIGHTS (GRPs)

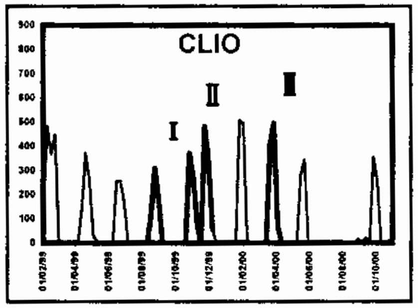

Fig. 16

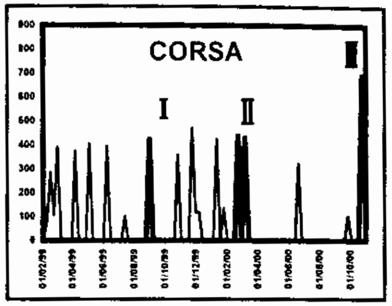

Fig. 17

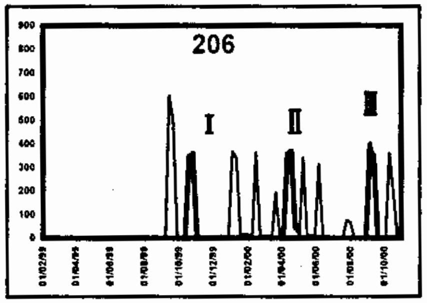

Fig. 18

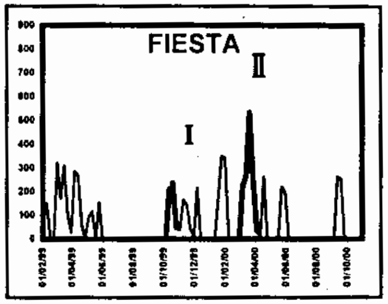

Fig. 19

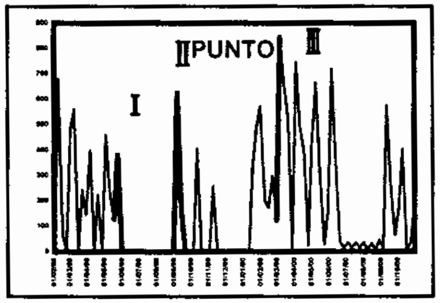

Fig. 20

Fig. 21 - 25 CORRELOGRAMS FOR ERRORS FROM THE INTERVENTION MODELS

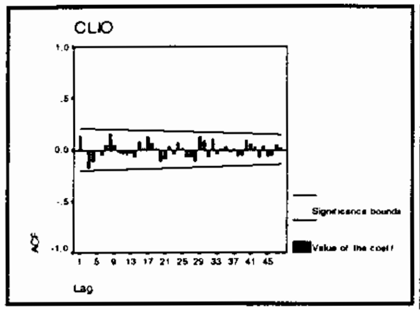

Fig. 21

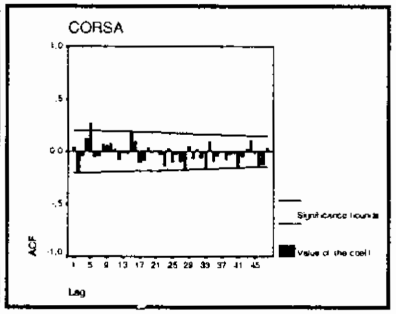

Fig. 22

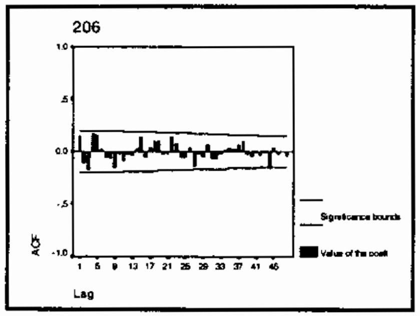

Fig. 23

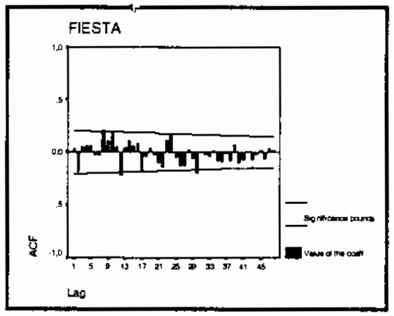

Fig. 24

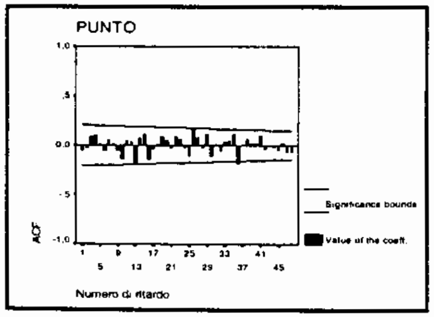

Fig. 25

Fig. 26 - 30 ERRORS FROM THE INTERVENTION MODELS

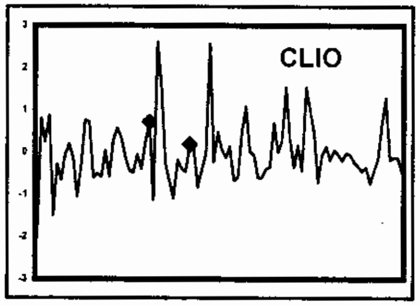

Fig. 26

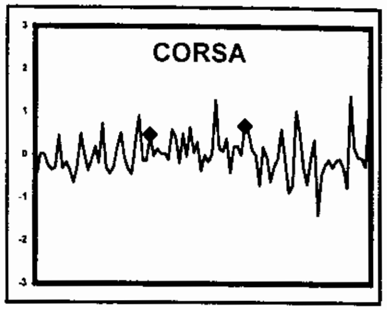

Fig. 27

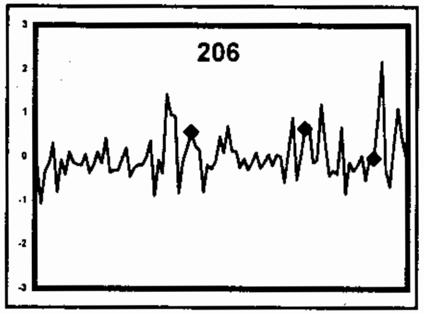

Fig. 28

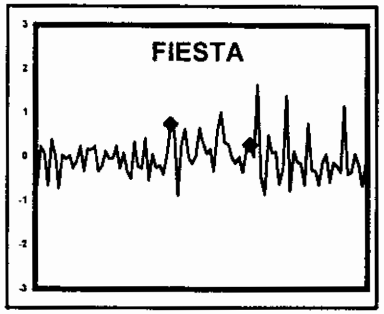

Fig. 29

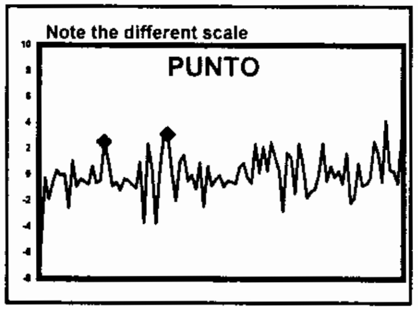

Fig. 30